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Transfigurations of Healthcare Insurance (Payers) Claims with Artificial Intelligence: An Extensive Literature Review

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Abstract: Health Insurance (HI) pays for medical as well as surgical expenditures incurred by the insured person, thereby rendering financial safety against the expensive costs related to Healthcare (HC) services. HC costs are effectively managed via the process of Healthcare Insurance Claims (HICs), where insured individuals submit claims to their insurance providers. This system of claims management streamlines the payment process and promotes better usage of HC resources by mitigating the financial barriers to accessing care. Although numerous benefits are attained, the HICs process could be time-consuming and error-prone. Delays for both patients and HC providers are often caused by errors. These issues can be solved more efficiently by integrating Artificial Intelligence (AI) into the claims process. Moreover, subsets of AI like Machine Learning (ML) and Deep Learning (DL) play a noteworthy role in enhancing the speed of HICs. These technologies can examine enormous data, detect patterns, and make predictions, further enhancing the claims process's efficiency. By knowing the objective, this review explains the transfigurations of HICs through AI, concentrating on key aspects like Fraud, Waste, and Abuse (FWA) prevention, real-time claim adjudication, and predictive analytics. Additionally, the challenges of AI in HICs are also discussed in this review paper.

Keywords: Healthcare insurance claim, Artificial Intelligence, Machine Learning, Deep Learning, claim adjudication, Predictive Analytics, and Convolutional Neural Network.

1. INTRODUCTION

The expenses of the patients in recent years have increased due to the increasing costs and difficulties of medical treatments. This can be tackled by health care insurance claim, which covers patients' expenses associated with their treatment and assists in receiving necessary care. This confirms that the claims data are broadly utilized for HC investigations. Claims data is known as the information associated with bills (claims) that HC practitioners submit to third-party payers. Information regarding medical diagnoses, surgeries, and treatments, as well as prescription information, is often encompassed in such claims [1].

The claim data show information regarding medical diagnoses, surgeries, and treatments, and also collect data on services received by patients enrolled in an HI plan and costs related to each service item [2]. The claims data from the insurance process has undergone significant transformations in the rapidly progressing landscape of HC, driven by technological improvements and the increasing complexity of patient care [3]. The advantages of insurance claim analytics in HC are explained in Figure 1 [4].

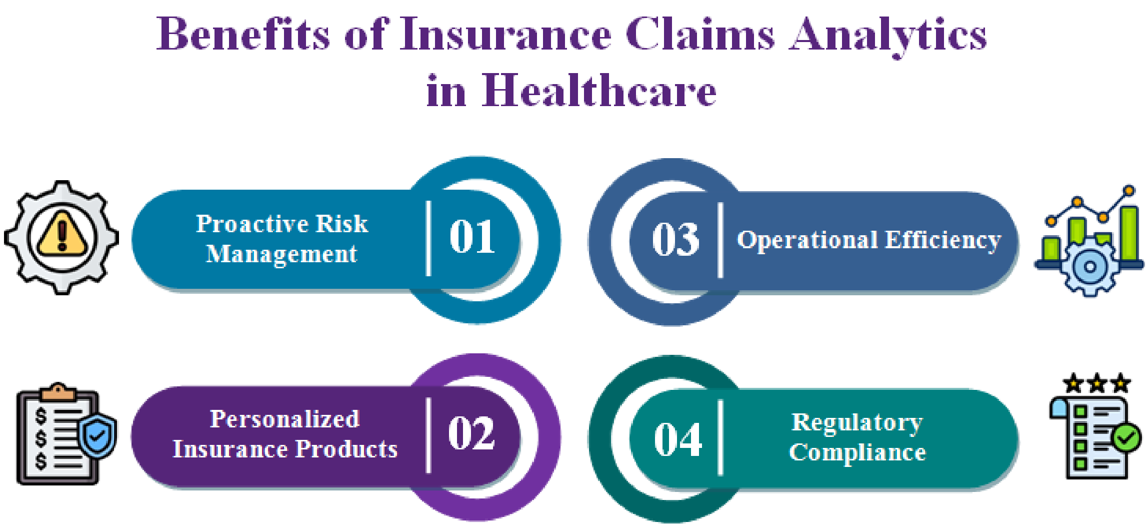

Figure 1: Advantages of insurance claim analytics in healthcare

It is clear from Figure 1 that both brokers and policyholders gain from the use of insurance claims analytics, which not only promotes the claims procedure but also supports innovation and advancement in the HC insurance sector. However, the management of HICs is challenging, marked by manual data entry, prolonged processing times, and frequent inaccuracies [5]. Also, for managing claims, HC insurance payers, encompassing insurance companies, Health Maintenance Organizations (HMOs), and government programs like Medicare and Medicaid, have historically depended on traditional methods [6, 7]. But, these methods, while effective to some extent, often suffer from inefficiencies, errors, fraud, and delays. In this situation, the industry is revolutionized by the combination of AI in HICs. To streamline and optimize the claims process, AI technologies like ML [Subsets of AI], DL [Subsets of AI], and predictive analytics are being used [8, 9]. These technologies promise to bring significant benefits not only to payers but also to HC providers, patients, and the overall HC system [10]. Anomalies, such as inconsistent billing or fraudulent claims, can also be detected by the AI systems, thereby reducing the risk of financial losses for payers and ensuring that claims are processed more accurately [11,12]. The ways that AI enhances fraud detection in medical claim processing are explored in Figure 2 [13].

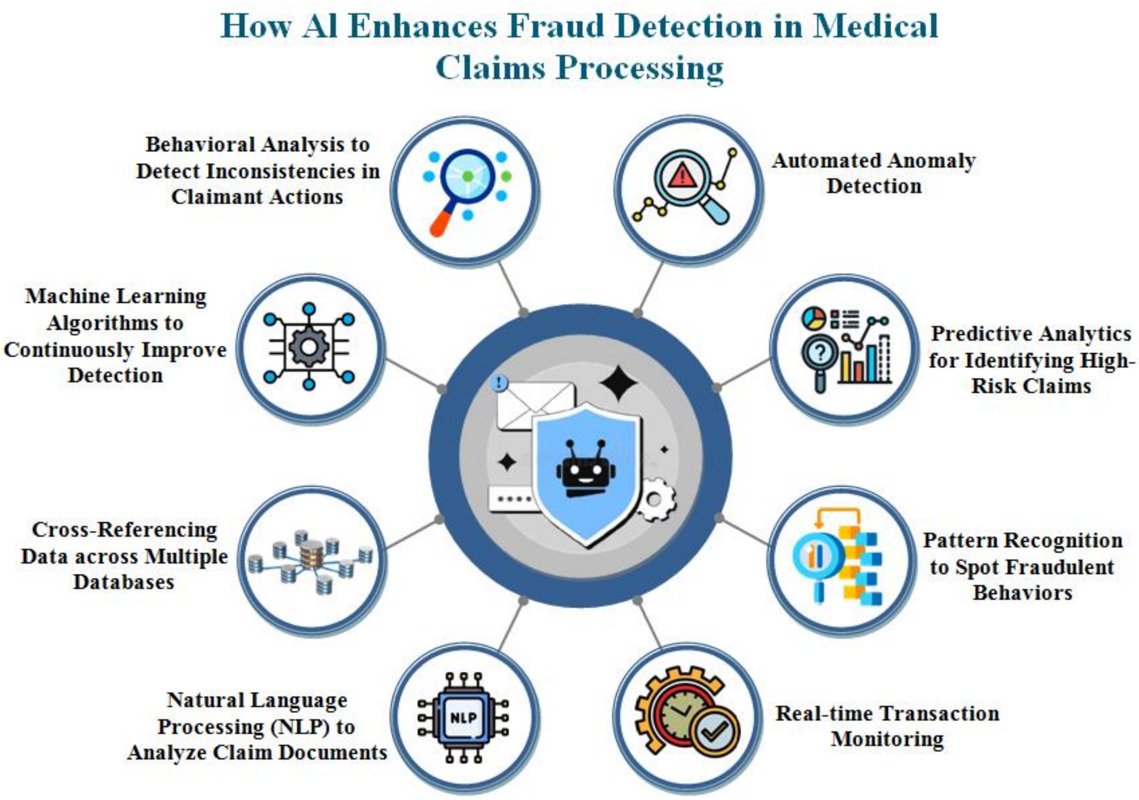

Figure 2: Ways that AI enhances fraud detection in medical claim processing

Moreover, AI-powered predictive models can assist payers in detecting high-risk claims early on, facilitating them to prioritize these cases and take appropriate action to prevent fraud or unnecessary expenditures [14]. Thus, when AI is used for HICs, substantial cost savings are expected. AI mitigates operational inefficiencies and administrative expenses by automating repetitive processes and increasing accuracy. To fund creative HC solutions and enhance patient care, these savings can be used [15].

The present review paper is arranged and classified using the forms given after the introduction in "***Section 1***". The study subjects and article selection methodology are first explained in "***Section 2***". "***Section 3***" talks about how AI is being employed to transform HI (payers) claims. Lastly, "***Section 4***" offers the study's appropriate summary to determine the exact outcome of the investigation. "***Section 5***" closes the review study with pertinent findings and future directions.

2. DEVELOPING RESEARCH QUESTIONS AND ARTICLE SELECTION STRATEGY

Every research work begins with a Research Question (RQ), which directs data collection, analysis, and literature searches. The establishment of an RQ must be included in any investigation, including a review or thesis. RQ is a key stage in the entire research process. Furthermore, it is found that the study has design flaws that are more challenging to fix in the absence of a strong question.

2.1. RQs

RQ plays a significant role in the conversion of HICs with AI. They help guide the research process, ensuring that it is systematic, focused, and pertinent. The developed RQs are demonstrated in Figure 3.

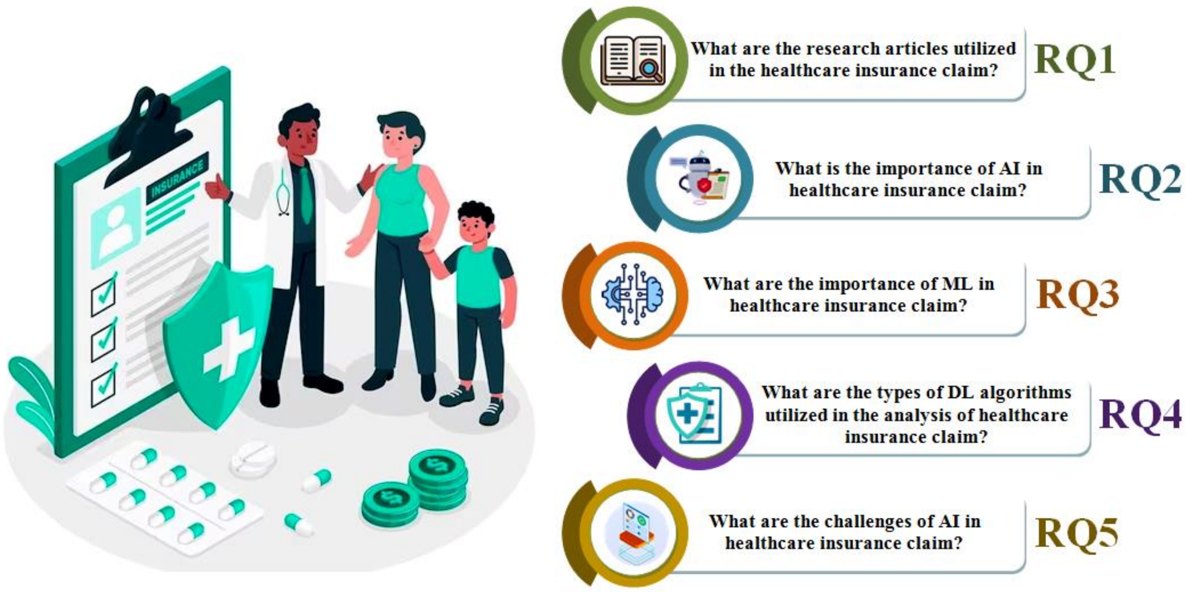

Figure 3: Established RQs

It is clear from the above RQs that these questions are vital for systematically exploring the potential of AI in transforming HICs, explaining challenges, and maximizing benefits for both insurers and policyholders.

2.2. Article selection strategy

The goal of an article selection approach is to find pertinent papers to show that the investigation is impartial. The correctness and dependability of the study rely heavily on a well-designed methodology. Whether it is a review, thesis, or research, using related keywords in the research process is essential when creating an article selection strategy. This kind of approach is crucial for finding objects that fit the objectives. The inclusion and exclusion selection criteria are explained in Figure 4.

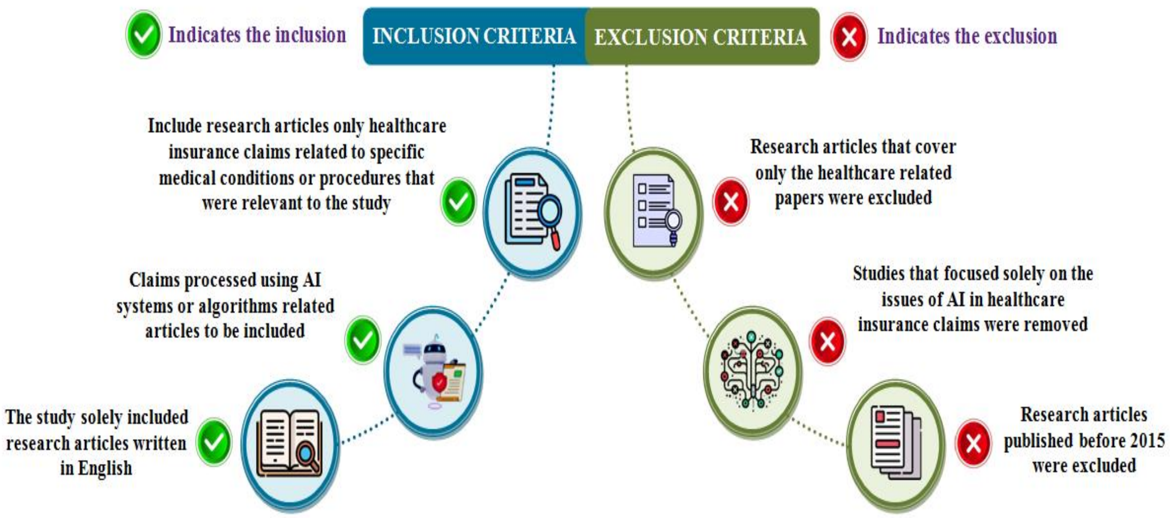

Figure 4: Inclusion and exclusion selection criteria

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Further, explaining the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flowchart is essential. PRISMA assessed that the authors rendered a complete description of why the review was carried out, what they achieved, and what they identified. It signified the number of identified records, the included as well as excluded data, and the reasons for the exclusions. Thus, Figure 5 illustrates the PRISMA framework.

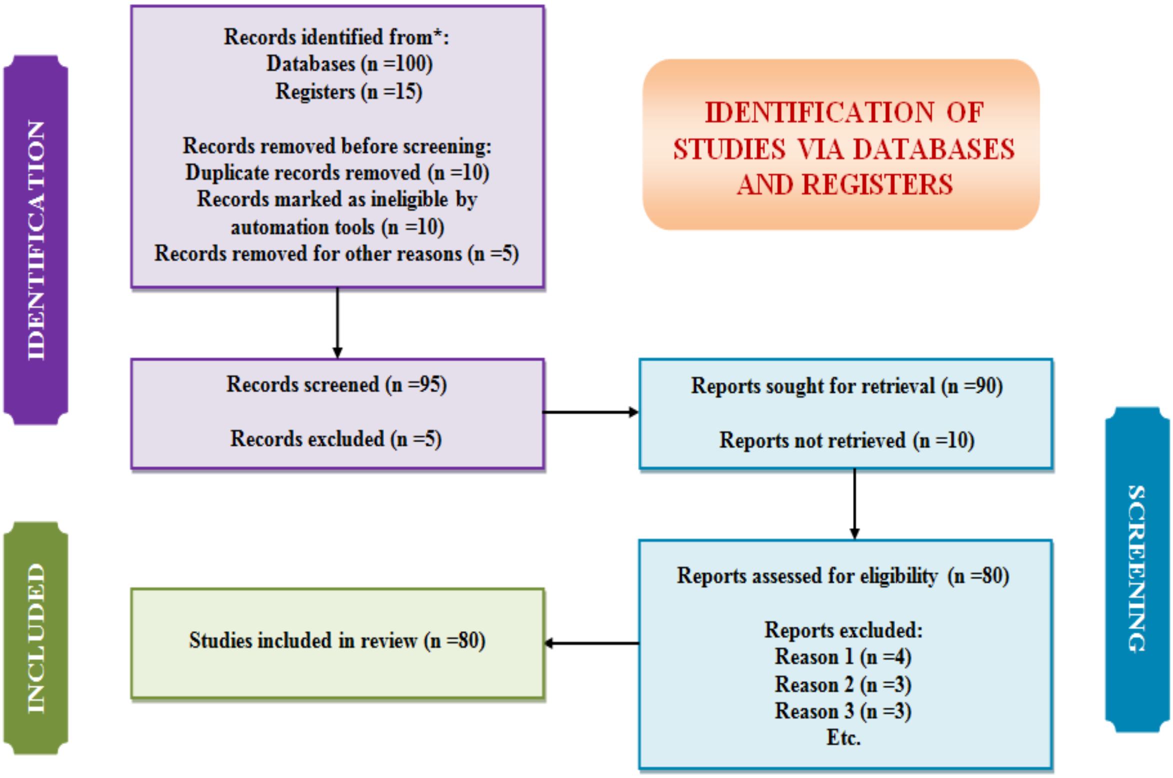

Figure 5: PRISMA framework

2.2.1. Resources of search

While executing a literature evaluation for a research section, selecting the appropriate databases and resources and assessing the publication's reliability are vital. The following contains comprehensive details about the sources, database options, database perception, and paper selection.

Sources: By using a number of academic search engines, including Google Scholar, Elsevier, IEEE Xplore, and Springer, the data on the research topic was gathered. In the analysis, the research articles from 2015 to 2025 were included.

Database options: Important databases like WOS, SCIE, and Scopus assisted in finding research publications.

Database perception: Despite the prevalence of significant databases, journal-based databases that found articles pertinent to the goal stood out. Noteworthy benefits regarding the presentation and content of the research were provided by the chosen databases.

Selection of papers: For the systematic review, eighty papers were chosen ultimately. Centered on predetermined standards, the articles were chosen carefully. Figure 6 graphically displays the search results for this literature review.

	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Science Direct	0	0	0	0	2	0	1	0	0	0	0
Scopus	0	1	0	1	3	2	3	4	4	5	0
Web of Science	0	0	0	0	0	0	1	1	0	0	0
IEEE	0	0	1	1	0	0	1	1	0	0	0
Others	1	0	3	0	1	6	5	8	9	12	3

Figure 6: An illustration of the literature review's search results

3. LITERATURE REVIEW

HICs have turned out to be increasingly complex, owing to the rising volume and the numerous claims that need to be processed. The AI's integration in HC claim processing has illustrated remarkable potential for augmenting efficiency, accuracy, and cost-effectiveness. AI, through ML and DL, plays a pivotal role in numerous aspects of HICs. The implementation of AI in HICs is not without challenges. Data privacy and security concerns, the necessity for high-quality and diverse training data, and the potential for algorithmic biases are substantial hurdles that need to be explained.

3.1. OVERVIEW OF HEALTHCARE INSURANCE CLAIMS

A HIC is the procedure by which insured persons or HC providers ask an insurance company to reimburse them for medical services delivered [16]. Following medical treatment, the provider files a claim with the insurance company, encompassing the services rendered, diagnosis, course of treatment, and related expenses [17]. The claim is then examined by the insurance provider to ensure that it is accurate, medically necessary, and covered by the policy. If the claim is accepted, the insurer may reimburse the insured or the provider, depending on the conditions of the policy [18]. Claims that have been rejected may be appealed or amended and resubmitted for review. This procedure guarantees that HC providers and insured persons receive payment according to the insurance plan's provisions [19].

Kubo, *et al* [20] explained the National Database of HICs and Specific Health Checkups of Japan (NDB) with the outline and patient-matching approach. The study concentrated on information from HICs for hospital stays, combination diagnostic tests, outpatient care, and prescription drug dispensing that were submitted between April 2013 and March 2016. As per the findings, fewer patients in each age and sex group were recognized utilizing the ID0 variable than those detected utilizing the ID1 variable. By utilizing the ID0 variable, the amount of duplicate records might be decreased by 5.8% for male patients and 6.4% for female patients.

Madan, *et al* [21] defined the HI sector and claims in India as an investigation of its performance. The HI industry's performance in India was explored in this study. A strong correlation between insured loss and earned premium was exhibited by the study's conclusions. Although the sector's earnings were increasing at a 27% compound annual growth rate, it was still unable to generate underwriting profit. Money was continuously lost by the insurance industry. Hence, ideas must be implemented to minimize losses if earnings were not being made.

Jin, *et al* [22] explained the clinical investigation utilizing the HC claims database. A database was created in the case of the NHIS in 2006 and then provided to researchers in 2010. A thorough and long-term understanding of insurance items acted as the foundation for the interpretation of studies done utilizing claims data. As per the research, there were several samples in the claims data, signifying a higher level of statistical power. However, establishing a causal relationship was challenging for the reason that these data only illustrated a phenomenon.

Yang, *et al* [23] analyzed the HICs over diverse periods for predicting days in the hospital. The data were windowed at 4 diverse timeframes (bi-monthly, quarterly, half-yearly, and annual) in the applied approach for creating frequently spaced time series features that were derived from such events. 4 related prediction methodologies were produced. The half-yearly model's superiority was shown to be more noticeable in the elderly subpopulation. A bagged Decision Tree (DT) methodology could predict "no hospitalization" as opposed to "at least one day in hospital" with a 0.426 Matthews' Correlation Coefficient (MCC).

Enamul, *et al* [24] identified HIC fraud utilizing a mixture of clinical concepts. To define the fraud detection issue, a minimal set of conclusive claim data, including medical diagnostic and procedure codes, was employed. When analogized to MCC + RPCA, MOD, and Baseline, MCC and MCC + LSTM produced better and more constant outcomes for a range of concept sizes and replacement probabilities. The accuracy, precision, and recall scores attained by the MCC + LSTM were 59%, 61%, and 50%, respectively.

Alex, *et al* [25] explained the social determinants of HIC denials for preventive care. From Symphony Health Solutions' Integrated DataVerse, the claims and remittance data during 2017-2020 were used in this cohort study of patients insured via their employers or the ACA Marketplaces. The analysis was conducted between January and July 2024. In this study of 1,535,181 patients looking for preventive care, the renunciations of insurance claims for preventive care were more likely among at-risk patient populaces.

Dominik, *et al* [26] investigated the data linkage of German statutory HICs data and care needs evaluations prior to a population-centered study on nursing home admission. In a deterministic record linkage, the primary variables of area, sex, date of birth, and care level were used. Records as of 2 federal states couldn't be matched owing to incomplete data. Linkage rates were lower in areas where more persons had the same qualities. The generated dataset revealed slight variations in age, sex, and care level when analogized to the original cohort.

Sony, *et al* [27] explained the income disparity as well as HC usage with the lessons as of national HIC data of Indonesia. The claims data were gathered from JKN customers during 2015-2016. To examine the consumption of health services by subsidized and non-subsidized users, the Ordinary Least Squares estimate methodology was utilized. According to the analysis, subsidized users were more likely than non-subsidized consumers for accessing primary HC services. When analogized to other users, secondary and tertiary health care services were used more often by non-subsidized consumers.

3.2. IMPORTANCE OF AI IN HEALTHCARE INSURANCE CLAIMS

AI is converting HICs by streamlining and enhancing the entire procedure [28]. AI could be utilized by insurance companies to automate claim processing and verification, saving time and effort compared to manual review. Faster claim approvals result from this, which benefits patients and insurers alike by rendering immediate reimbursement for medical care [29, 30]. Moreover, AI-powered systems are better capable of identifying false claims, shielding insurance companies from large financial losses [31]. AI can also detect patterns as well as trends by analyzing enormous data, enabling insurers to offer personalized and fair premium rates [32]. Efficiency, accuracy, and customer satisfaction were augmented by the combination of AI in HICs, ultimately converting the industry's landscape.

Aneehika, *et al* [33] enhanced the HIC processing via AI and Data Analytics. The effects of AI-driven systems on processing times, mistake rates, and customer satisfaction were assessed using a mixed-methods approach that included case studies from top insurers. Notable increases in operational accuracy and efficiency and improved client experiences were shown by the results. Nevertheless, challenges like algorithmic bias, data privacy, and legacy system integration continued to exist.

Jeshwanth, *et al* [34] described the revolutionizing claims processing in the Healthcare Sector (HS) with the increasing role of automation as well as AI. It assessed how automation and AI could convert the claims processing industry in numerous ways, including streamlining operations, mitigating human error, and facilitating real-time claim processing. For numerous HS stakeholders, the research's conclusions had significant consequences.

Ramesh, *et al* [35] explained the AI-driven intelligent document processing for HC and insurance. By combining RPA and Natural Language Processing (NLP), IDP decreased error rates by 90% and document processing time by 80%. Case studies from leading hospitals and insurers illustrated the AI's ability to improve patient care, streamline claims processing, and streamline operations. By using a planned and staged approach, businesses might smoothly migrate to AI-driven automation, thereby resulting in faster processing, lower costs, and more robust fraud detection.

Shey, *et al* [36] described a decision support system with AI and NLP for diminishing the deduction rate of HICs. By employing a natural language technique called Latent Dirichlet Allocation (LDA), the medical records of patients were examined. The experiment carried out on diverse medical departments demonstrated that the predictive methodology could yield correct findings and diminish the HICs' deduction by more than 41.7%.

Krishna, *et al* [37] explained the enhanced claims processing along with improved analytics for rapid and accurate claims handling in HC or insurance. Although applying advanced analytics rendered numerous organizational benefits, including process standardization, cost savings, and enhanced decision-making, there were drawbacks. According to the findings, a unified strategy that included training and modernizing outdated technologies was required to lower the above-mentioned challenges. It also ensured that the facilities met security standards and encouraged an innovative culture inside the companies.

Calvin, *et al* [38] described the confirmation of the reliable utilization of AI as well as big data analytics in HI. Legal criteria must be implemented in addition to encouraging and providing incentives for insurers to embrace a human-centered framework in the development and application of big data analytics and AI. As per the analysis, the usage of such analytics was likely to worsen already-existing inequities, increase the number of disconnected data systems, and undermine credibility and trust unless an ethically supportive environment was in place.

3.2.1. ML algorithms' importance in different aspects of healthcare insurance claims

ML, a subset of AI, is revolutionizing the processing of HC claims by solving important problems, including fraud, waste, abuse prevention, claim automation, real-time claim adjudication, and forecasts [39,40]. To identify patterns suggestive of fraudulent activity, ML can reduce financial losses from FWA by using sophisticated algorithms [41]. Insurance firms are able to diminish risks and distribute resources more effectively through a proactive approach. Another essential aspect is claim automation, where ML-driven solutions enhance the processing and verification of claims, drastically lowering the necessity for manual intervention and accelerating the approval process [42, 43].

DT, Support Vector Machine (SVM), Naïve Bayes, Random Forest (RF), Logistic Regression, Linear Regression, eXtreme Gradient Boosting (XGBoost), and K-Nearest Neighbors (KNN) are some of the ML algorithms employed in diverse aspects like fraud waste, abuse prevention, claim automation and real-time claim adjudication, and predictions for HICs [44]. The research articles associated with the ML algorithms in different aspects of HICs, with their dataset, findings, and limitations, are explained in Table 1.

Table 1: Research articles related to the ML algorithms in different aspects of healthcare insurance claims, with their dataset, findings, and limitations

<table>
<tr><th rowspan="2">Authors' name</th><th rowspan="2">Aspects</th><th rowspan="2">ML techniques</th><th rowspan="2">Datasets</th><th colspan="2">Findings</th><th rowspan="2">Limitations</th></tr>
<tr><th colspan="2">R-squared values</th></tr>
<tr><td>Ashrafe, et al [45]</td><td>Prediction of HICs</td><td>XGBoost and RF</td><td>Kaggle</td><td colspan="2">XGBoost: 79% and RF: 77%</td><td>Smaller sample sizes augmented sampling bias as the data mightn't signify the populace accurately.</td></tr>
<tr><td rowspan="2">Sharifa, et al [46]</td><td rowspan="2">Detection of fraud in HICs</td><td rowspan="2">Naïve Bayes</td><td rowspan="2">Datasets from public healthcare datasets and synthetic data</td><td>Accuracy (%)</td><td>Classification error</td><td rowspan="2">There might be infrastructure challenges when applying the Naïve Bayes methodology in practice in the real world.</td></tr>
<tr><td>91.79%</td><td>1.09%</td></tr>
<tr><td rowspan="2">Ritesh, et al [47]</td><td rowspan="2">Prediction of claim denial</td><td rowspan="2">Gradient Boosted Trees (GBT)</td><td rowspan="2">A large dataset of historical claims from a national payer</td><td>Sensitivity</td><td>Specificity</td><td rowspan="2">The model was trained on data from a single national payer, limiting its applicability to other payers.</td></tr>
<tr><td>0.78</td><td>0.95</td></tr>
</table>

Saravanan, *et al* [48]	Detection of HI Fraud and claim adjudication time	BOXGBoost model	HI dataset	***Accuracy (%)***	***AUC***	Deploying the model in real-world settings might face challenges like integration with prevailing systems.
				98%	0.994	
Robert, *et al* [49]	Fraud detection	Genetic SVMs (GSVMs)	National HI Scheme claims dataset	***Classification accuracy***		There was a risk of overfitting in which the methodology performed better on the training data but might not generalize well to modified data.
				80.67 % (Linear)		
Nur, *et al* [50]	Prediction of HICs	Gradient boosting	HICs	***Recall (%)***	***Accuracy (%)***	Any inconsistencies or errors in the data could affect the model's performance.
				85%	85%	
Elvan, *et al* [51]	Fraud detection	XG boost	Medicare Part B dataset	***AUC***	***Precision***	XGBoost was a powerful algorithm that could be complex and necessitate significant computational resources.
				84.563	0.86	
Richard, *et al* [52]	Medicare fraud detection	RF	Medicare dataset	The results exhibited that the 90:10 class distributions had the best outcomes with 0.87302 AUC, whereas the 99.9:0.01 distributions had the lowest results.		The dataset had a substantial class imbalance, with fraudulent claims being a very small proportion of the total claims.

Seema, *et al* [53] explained the predictive analysis for claims in the insurance industry by employing ML. For this experimental study, a number of characteristics, such as age, gender, blood pressure, and so on, were gathered. As per the data, the RF algorithm had the best accuracy of any algorithm at 90%. The AUC

was also the highest of all at 94%. It was found that insurers were utilizing ML for enhancing operational effectiveness across the board, from registering claims to settling them.
Stephen, *et al* [54] described the accurate classification of carotid endarterectomy indication utilizing physician claims and hospital discharge data in HC. By reviewing the charts before being linked to hospital discharge data and physician claims, the symptomatic status was determined. Sensitivity and specificity were used to gauge how accurate the rule-centered classification by discharge diagnostic codes was. Methodologies that used physician claims data were considerably more sensitive at matched 98.6% specificity: RF 78.8% (69–88%) and elastic net 69.4% (59–82%).
Manywanda, *et al* [55] explained the sustainability of ML in the health claims automation in the Kenyan insurance company. KNN, Naïve Bayes, and linear discriminant analysis were the ML techniques employed in the analysis. Among those mentioned for assessing the veracity of claims, KNN was found to be the most effective methodology with a 99.9% accuracy rate. Superior results were yielded by KNN in both small and large datasets.
Jenita, *et al* [56] described the analytical investigation on fraud detection in HIC data by employing ML classifiers. To analyze SVM, Naive Bayes, and two traditional ML classifiers, including k-means clustering, a dataset was used for HC provider fraud detection. The Naive Bayes classifier produced 90% precision, 97.7% recall, and 94.6% accuracy for 10-fold cross validation, whereas the results were 92% precision, 98% recall, and 95.6% accuracy for 66% splits.
Anwar, *et al* [57] explained the computational intelligence framework to detect medical insurance costs. In the applied research strategy, linear Regression, Support Vector Regression, Ridge Regressor, Stochastic Gradient Boosting, XGBoost, DT, RF Regressor, Multiple Linear Regression, and KNN were employed. From the KAGGLE repository, a dataset of medical insurance costs was obtained. According to the results, the Stochastic Gradient Boosting (SGB) methodology performed better than the others with 86% accuracy, 0.0.858 cross-validation value, and a 0.340 RMSE value.
Onyango, *et al* [58] described the application of ML for detecting fraudulent maternal medical claims. From the insurance company, the information was gathered and underwent several phases of data collection. According to the findings of the performance benchmark and evaluation, the gradient boost exhibited higher performance with a 90.0% accuracy and a 95.0% AUC. The accuracy of logistic regression was 59%.

3.2.2. DL algorithms' importance in different aspects for healthcare insurance claims

By enhancing FWA prevention through advanced anomaly detection and predictive modelling, DL algorithms play a substantial role in the HC insurance industry [59, 60]. DL algorithms also streamlined claim automation by automating data extraction and decision-making processes, thus facilitating real-time claim adjudication with intelligent document processing and rapid decision-making capabilities [61]. DL algorithms also enhance forecasts for HICs by leveraging historical data and sequential deep regression techniques for accurate predictions [62]. These applications collectively make a contribution to increased efficiency, accuracy, and cost savings, ensuring a more robust and reliable insurance ecosystem. The DL algorithms utilized in the analysis of HICs were Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNN), Long Short Term Networks (LSTM), Generative Adversarial Networks (GANs), and Autoencoders [63]. The research articles associated with the DL algorithms in different aspects of HICs, with their dataset, findings, and limitations, are explained in Table 2.

Table 2: Research articles related to the DL algorithms in different aspects of healthcare insurance claims with their dataset, findings, and limitations

<table>
<tr><th rowspan="2">Authors' name</th><th rowspan="2">Aspects</th><th rowspan="2">DL techniques</th><th rowspan="2">Dataset</th><th colspan="2">Findings</th><th rowspan="2">Limitations</th></tr>
<tr><th colspan="2">Accuracy (%)</th></tr>
<tr><td>Ranu, et al [64]</td><td>Prediction of fraud insurance claims</td><td>GANs</td><td>Tabular data related to HICs</td><td colspan="2">CTGAN: 95.96%</td><td>GANs were complex models that required significant computational resources and expertise to train effectively.</td></tr>
<tr><td rowspan="2">Navatha, et al [65]</td><td rowspan="2">Prediction of insurance claims</td><td rowspan="2">LSTMs</td><td rowspan="2">Claims paid dataset</td><td>MSE</td><td>RMSE</td><td rowspan="2">DL models require enormous, high-quality data for training.</td></tr>
<tr><td>2.92E+09</td><td>5.40E+04</td></tr>
<tr><td>Mounika, et al [66]</td><td>Detection of HIC fraud</td><td>LSTMs</td><td>medical diagnosis and procedure codes</td><td colspan="2">MCC + LSTM achieved recall, accuracy, and precision scores of 50%, 61%, and 59%, correspondingly, on the Information for inpatient claim details.</td><td>The approach involved complex algorithms and models, which required significant computational resources.</td></tr>
<tr><td rowspan="2">Sam, et al [67]</td><td rowspan="2">Prediction of HIC</td><td rowspan="2">Neural Network (NN)</td><td rowspan="2">real-world clinical dataset (MIMIC-III)</td><td>MAPE</td><td>Accuracy (%)</td><td rowspan="2">ANNs were deemed "black boxes" because their decision-making procedures were not easily interpretable.</td></tr>
<tr><td>NN: 12.15 (Feedforward)</td><td>NN:87.85 (Feedforward)</td></tr>
<tr><td rowspan="2">Jayanthi, et al [68]</td><td rowspan="2">Prediction of Medi-Claim</td><td rowspan="2">CNNs</td><td rowspan="2">open-source dataset on Kaggle</td><td>Accuracy (%)</td><td>AUROC score</td><td rowspan="2">CNN could be susceptible to adversarial attacks, where smaller intentional perturbations to the input data could cause wrong predictions.</td></tr>
<tr><td>0.9</td><td>0.8</td></tr>
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Michael, *et al* [69] explained the FWA detection from healthcare claims by employing unsupervised DL methods. To identify claims with abnormal procedure codes suggestive of FWA, deep autoencoder experiments were used. The outcomes were compared with a baseline density-centered clustering methodology. The autoencoder methodology, which was trained on one lakh claims, had 0.87 precision, 1.0 recall, and 0.93 F1-scores on the synthetic outlier test dataset, whereas these metrics showed 0.36, 0.86, and 0.51 on the manually annotated outlier test dataset, respectively.

Isaac, *et al* [70] described the autonomous investigation of healthcare insurance reports via deep neural networks for identifying severe claims. Various rebalance algorithms were employed to address the issue of unbalanced data (too few observations were linked to a positive label). Though the outcomes were comparable (fitting the network's parameters takes around four times less computing time), CNN techniques performed worse than LSTM techniques.

Byung, *et al* [71] explained the deep claim with the payer response prediction as of claims data with DL. A (lower-level) context-dependent compact representation of patients' past claim records was applied by efficiently learning complex dependencies in the (higher-level) claim inputs. The most notable improvement in Deep Claim's ability to forecast claim rejections over properly chosen baselines was a 22.21% relative recall gain (at 95% precision) on Health System A, suggesting that Deep Claim could detect 22.21% more denials compared to the optimal baseline system.

Precious, *et al* [72] described the DL approach for HC insurance fraud detection. To enhance these methodologies' interpretability, Locally Interpretable Model-agnostic Explanations (LIME) were utilized. As per the findings, the ANN showed better outcomes with a 0.57 F1-score, 0.94 accuracy, 0.78 precision, and 0.45 recall. The LSTM was highly effectual in lowering false negatives, even if CNN was superior in accuracy.

3.3. CHALLENGES OF USING AI IN HEALTH INSURANCE CLAIMS

When integrating AI into the processing of HICs, there are several difficult challenges to overcome [73]. Most importantly, data security and privacy are crucial since sensitive medical data necessitates strong protection against breaches and misuse [74]. The complexity of health data, including unstructured data from handwritten notes and medical records, is another challenge [75]. Furthermore, regulatory compliance must be rigorously adhered to AI models requiring constant updates to align with evolving legal standards [76].

David, *et al* [77] explained the AI's power with the richness of HC claims data, with the opportunities as well as challenges. Identifying complex patterns in high-dimensional datasets could cause the development of early illness predictors or a more proactive approach to providing individualized preventive services.

Challenges: AI has significantly impacted the procedure of obtaining HI coverage. AI improved or could improve fraudulent claim identification, claim adjudication, and claim submission. However, AI's predictive power was also utilized to unfavorably modify insurance rates based on combinations of individual traits.

Jeshwanth, *et al* [78] described the revolutionizing claims processing in the HS with the automation and AI's expanding role. Insurance firms and HC providers had to negotiate a challenging environment full of interoperability problems, data security issues, and regulatory compliance issues.

Challenges: The claims processing environment was made even more complex by the issues with interoperability. Numerous HC institutions rely on various legacy systems that are incompatible with one another. Along with impeding the smooth flow of information, inadequate connections augmented administrative workloads by manually entering and validating data across several systems.

Malapati, *et al* [79] explained fraud detection in medical insurance claim systems using ML. By using metrics like accuracy, precision, recall, and F1-score, the methodology's performance was assessed. As per the findings, the optimized SVM model greatly improved the detection of fraudulent claims in comparison to baseline models.

Challenges: Due to the insurance industry's explosive growth, scalable fraud detection systems that adjust to growing data quantities and changing fraud trends were required. Despite the utilization of ML, security was lacking.

Shashank, *et al* [80] described an intelligent ML framework for fraud detection in medical claim insurance. When analogized to traditional fraud detection frameworks, the findings exhibited noteworthy gains in accuracy, precision, recall, and F1-score. Besides, a comparison with various ML algorithms was carried out, confirming the method's supremacy in this field.

Challenges: K-means clustering didn't depend on labeled data, making it compatible for fraud detection. It could be challenging as well as expensive to obtain labeled instances of fraudulent claims.

4. SUMMARY OF THE REVIEW

By improving real-time decision-making, fraud detection, and efficiency, AI's revolution in HIC processing is transforming the sector. AI-driven systems lessen reliance on manual procedures by enabling real-time adjudication while maintaining accuracy and transparency. By identifying questionable claim trends and reducing monetary losses, predictive analytics improves fraud prevention in claim processing. AI automation diminishes operational expenses and administrative strains by streamlining procedures. With these benefits, applying AI presents a number of difficulties like dangers to data security, biases in algorithms, and complicated regulations. For the shift to AI-driven claim processing, strong data governance procedures, funding for AI research, and tactical cooperation between insurers, HC providers, and tech developers are all necessary. In order to make the review more interesting, the categorized RQs' answers have been discussed in detail in the following areas:

- ✓ ***Research articles utilized in the healthcare insurance claims:*** This question's answer was detailed in Section 3.1 with different relevant research articles from reference numbers 20th to 27th.
- ✓ ***Importance of AI in healthcare insurance claims:*** For this question, the significance of AI in HICs was detailed in section 3.2.
- ✓ ***Importance of ML in healthcare insurance claims:*** The significance of ML in HICs was explained in section 3.2. (Reference 33rd to 38th).
- ✓ ***Types of DL algorithms utilized in the analysis of healthcare insurance claims:*** The types of DL algorithms, including CNN, RNN, LSTM, etc., were discussed in different research articles in section 3.2.1.
- ✓ ***Challenges of AI in healthcare insurance claims:*** As per the question, the challenges of AI in HICs were explained in detail with the related research articles.

Thus, insurance companies should manage the constraints as technology develops while utilizing AI's potential to build a more dependable and adaptable claims processing system. The success of AI-driven changes in the HC insurance industry will depend on the ongoing development of AI as well as ethical and regulatory monitoring.

5. CONCLUSION

By increasing productivity, decreasing fraud, and facilitating real-time claim adjudication, the management of HICs has been revolutionized by AI. Automation brought about by AI-driven technologies like ML and predictive analytics mitigated the necessity for human interaction and accelerated the processing of claims. Fraud detection Algorithms were essential in spotting irregularities, preventing monetary losses, and guaranteeing legal compliance. Real-time adjudication enhanced transparency and client satisfaction by accelerating claim settlements. Because of predictive modelling, insurers were also able to evaluate claim risks and stop fraudulent claims before they happened. Despite advantages, 2 significant limitations were identified in the literature review of the research articles. Initially, AI models were trained on historical datasets that contain biases. These biases could cause incorrect claim denials if not properly addressed. Secondly, accurate and high-quality data could be required by AI models to function optimally. The reliability and effectiveness of AI-driven claim processing could be impacted by inconsistent, incomplete, or erroneous data. Future researchers should consider these 2 limitations and find solutions to avoid biases while utilizing the datasets. Overall, AI will turn out to be a vital tool for payers everywhere as the future of HC claims administration is destined to see elevated automation, wise decision-making, and enhanced regulatory compliance.

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